Social preferences for agricultural policy instruments: joint consideration of non-attendance to attributes in modelling discrete choice data

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Social preferences for agricultural policy instruments: joint consideration of non-attendance to attributes and to alternatives in modelling discrete choice data.

Abstract

This paper uses the choice experiment method to analyse social preferences towards a set of agricultural policy instruments that are likely to play a key role in the post 2013 design of the EU Common Agricultural Policy. It contributes to the choice experiment literature by incorporating different attribute processing strategies into stated choice models. By comparing models that consider attribute non-attendance for individual choice tasks and for the whole sequence of choices, we demonstrate the impact of different ways of accounting for attribute non-attendance on model performance and preferences. Additionally, we test if 'non-attendance to alternatives', which describes the elimination of alternatives due to the presence of attribute levels deemed unacceptable to a respondent, is a relevant information processing strategy in a choice experiment context. The results clearly show that individuals allocate attention over a reduced array of information and jointly apply decision strategies that involve attribute non-attendance and non-attendance to alternatives. The joint consideration of these information processing strategies results in a significant improvement of model fit to data, and in a better description of respondents' preferences.

Key words: Attribute processing strategies, Choice experiment, Common Agricultural Policy instruments.

Introduction

In modelling data from DCE surveys, respondents are typically assumed to be rational individuals, who maximize their utility by always choosing the alternative from a finite choice set that yields the highest utility. Assuming complete knowledge of all the alternatives, attributes and levels presented on the choice cards of a DCE, respondents are assumed to make trade-offs between *all* the attribute levels of the different alternatives when choosing the preferred alternative. In this case, the choices made by individuals would reflect fully compensatory behaviour.

However, a growing body of literature has shown that respondents ignore one or several attributes when making choices, reflecting non-compensatory decision rules. The phenomenon of respondents focusing on only a subset of attributes while making their choices is known as attribute non-attendance (ANA). Such behaviour was found to result in biased estimates of marginal utilities and welfare measures due to misspecification of the applied utility maximizing decision rules (e.g. Hensher et al. 2005, Campbell et al. 2008, Hensher and Greene 2010, Scarpa et al. 2010). For instance, if respondents do not pay attention to an alternative's price, estimates of marginal utility of income are lowered, which results in inflated measures of marginal WTP.

Respondents may choose to ignore attributes for a number of reasons (Alemu et al. 2012). The attribute may not contribute to the utility of a respondent and hence be irrelevant to the choice decision. Alternatively, the respondent's allocation of attention across attributes or alternatives may depend upon both the expected marginal benefits and marginal costs of further information processing (Cameron and De Shazo 2011).

This paper acknowledges the possibility of rationally adaptive behaviour to choice experiment information. We consider two types of decision rules. The first one is ANA, which usually occurs when some of the attributes in the choice set are not (or less) behaviourally relevant to certain respondents (Sælensminde 2006). In this context, we further investigate, how information on ANA should be incorporated into discrete choice models. We estimate models under different assumptions for reconstructing ANA at choice sequence level, and compare the results with those of models incorporating ANA at choice-task level, and with a baseline model that does not consider ANA at all. This represents an important contribution to an increasing number of studies on the role of ANA in modelling DCE data.

Additionally, we consider non-attendance to alternatives in the choice task. Similar to 'attribute non-attendance' where attributes are ignored because they are irrelevant to the choice decision (but may have been perceived and evaluated as not important by respondents and hence 'attended to'), 'non-attendance to alternatives' refers to situations where an alternative would be of no (or only very limited) importance to the final choice of preferred alternatives[i]. Non-attendance to alternatives can be triggered by either the presence of attribute levels, which are unacceptable; or by a composite mix of attribute that make the alternative inconsequential (Puckett and Hensher 2008). To account for non-attendance to alternatives, we estimate models, in which attribute information for certain alternatives is omitted based on information provided by respondents after each choice task. Specifically, respondents were asked after each choice task, whether any alternative was ignored because it contained one or more values (i.e., attribute levels), which they considered unacceptable. We interpret the presence of unacceptable attribute levels in alternatives as a criterion that rules out that these alternatives are being chosen. For this type of non-compensatory behaviour, we assume that respondents would follow a two-step procedure to carry out their choices. In the first step, alternatives are screened by an elimination-by-aspects (EBA; Tversky

1972) type process using the existence of unacceptable attribute levels as aspects. In the second step, the remaining alternatives are evaluated in detail either following a compensatory decision rule or using an ANA approach. Both ANA and non-attendance to alternatives can coexist. This is, to the best of our knowledge, the first time that non-attendance to alternatives as a non-compensatory decision rule is considered in addition to ANA.

In what follows, we first briefly review relevant previous studies, which investigated ANA. The methodological approach and the case study are subsequently described. Results are followed by a discussion, from which conclusions are drawn.

Previous studies

Several papers have recently investigated ANA to determine its impact on marginal rates of substitution and on welfare measures. Generally, evidence from the literature suggests that ANA matters, and understanding how respondents attended to information within the choice tasks allows improving the design of choice models and the quality of their results. Two main approaches to detecting and modelling ANA emerged; i) stated non-attendance (SNA), which aims to unveil ANA by directly asking respondents about the attributes they ignored in the choice task (Hensher et al. 2005, Carlsson et al. 2010, Scarpa et al. 2010).; ii) and analytical non-attendance, which makes use of analytical choice models to exogenously determine the degree of ANA from the choice data (Campbell et al. 2008, Scarpa et al. 2009). The analytical non-attendance approach offers the advantage of being applicable in the absence of self-reported information on attribute attendance, and as such does not rely on the accuracy of stated responses. However, recent findings from simulations conducted by Mariel et al. (2011) suggest that, under certain conditions of uncorrelated errors, SNA produces un-biased welfare estimates, whilst the analytical approach fails to do so. If a latent class approach is employed for inferring ANA analytically, the number of classes describing the ANA patterns increases exponentially with the number of attributes, rendering the approach infeasible for a large number of attributes (Hensher et al., 2012)[ii]. This complicates the use of this approach, especially when the available sample size is limited. Both the SNA approach and the analytical approaches were found to improve model fit, and Scarpa et al. (2011) found substantial validity and concordance between stated responses to ANA questions and analytically determined proportions of ANA. Hensher and Greene (2010), however, note that the two ways to identify attribute processing rules would 'not map very well'. It is therefore still an open question for research, which of both approaches is capable to better reflect the 'true' choice behaviour of respondents.

Within the SNA approach, the analyst can account for ANA either at each choice task individually (choice task level), or for the whole sequence of choices made by each respondent (choice sequence level or serial ANA). Most of the published studies on ANA disclosed attribute non-attendance at choice sequence level. However, Puckett and Hensher (2008) warn that respondents may show different patterns of ANA as they move through a series of choice tasks. This has been confirmed by recent studies, which compared SNA at choice task and sequence level (Scarpa et al. 2010, Meyerhoff and Liebe 2009). These studies suggest that the benefits of considering ANA at the choice task level in terms of model performance and efficiency of WTP estimates may outweigh the additional efforts associated with requesting ANA statements after each choice task instead of once after the choice experiment. In these studies, information on ANA at the choice sequence level has been reconstructed from statements at the choice task level based on the assumption that a respondent would have reported an attribute as 'ignored' only if s/he had stated to having ignored the attribute throughout the *whole* sequence of choices. This strong assumption may not apply. In fact, a respondent may declare to have ignored one attribute at sequence level, if s/he ignored it in only a subset of choices (for example, applying a majority rule). Therefore, it is necessary to scrutinize the findings from previous studies that compare ANA at choice task and sequence level. This can be achieved by analyzing the sensitivity of conclusions drawn from comparisons of models considering ANA at choice task and (reconstructed) sequence level, depending on the assumptions made for reconstructing ANA at the sequence level.

Hensher (2004) and Puckett and Hensher (2008) observed that ANA may extend to every alternative in every choice set, acknowledging that both non-attendance to alternatives and ANA can coexist. However, in their research they did not explicitly extend their empirical analysis to allow for non-attendance to alternatives, but instead focused on adding-up of common-metric attributes within each alternative. Puckett and Hensher (2008), in the context of freight distribution, observed that in addition to ANA respondents added up attribute levels along a common dimension (e.g., total travel time or total travel cost). They concluded that the two decision processes are common choice strategies among shippers and transporters, and importantly that they coexist.

The empirical findings from the published literature suggest that respondents commonly only focus on a subset of attributes or alternatives and may make use of different attribute processing strategies when choosing their preferred alternative. The subset of attributes/alternatives considered when making the choice can not only vary between respondents, but also within the choices made by the same respondents. Furthermore, for a single dataset several attribute or alternative processing strategies can coexist. Because there is evidence that the omission of considering alternative choice behaviours may bias estimates of preferences and welfare measures, it may be beneficial to simultaneously account for different decision rules. We explore this question in this paper by considering both non-attendance to attributes and non-attendance to alternatives in the analysis.

Empirical application

The data used in this research was derived from a DCE survey carried out in Andalusia in the South of Spain (Figure 1) to elicit respondents' preferences towards different Common Agricultural Policy (CAP) instruments, and in particular towards the budget share that society would optimally allocate to each of them.

The CAP has its roots in the 1950s and was created with the major goal of fostering agricultural production to generate a stable and affordable food supply whilst maintaining a viable agricultural sector in Europe. Many important reforms were imposed on the CAP in the last decades as a response to changes in farming practices, and to meet the demands of society as a whole. The reforms have led to a completely new policy structure that addresses, in addition to agriculture's productive capacity, the demand of EU citizens regarding the environment, food safety and quality, animal health and welfare, the preservation of the countryside, biodiversity and climate change (European Commission 2010b). Nonetheless, the evolution of the CAP with its successive reforms over time has resulted in a loss of social legitimacy of the policy (Salazar-Ordoñez et al. 2012). In the course of the current development of a new design of CAP post 2013, it has been argued that social legitimacy should be restored. As such, the CAP would be more widely accepted by society, who supports it financially. In this context, decision makers may use knowledge on citizens' preferences towards CAP payments and instruments in the negotiation process and development of the policy.

To elicit respondents' preferences towards different CAP instruments, and in particular towards the budget share that society would optimally allocate to each of them, we carried out a DCE using the following five instruments as attributes: direct payments; payments to farmers in disadvantaged areas; agri-environmental payments; payments to enhance the quality of life in rural areas and to contribute to the diversification of the rural economy; and payments aimed at improving the competitiveness of the agricultural sector. These attributes have been selected from a full list of CAP instruments, because they represent more than 90% of the current CAP spending in Andalusia, and were found to be pertinent to the design of credible future alternative design of CAP payments. According to Tangermann (2011), Jambor (2011) and Massot (2011), the most important challenges that the new CAP 2020 will have to face are: food security, environmental security and rural development. The instruments reflected by the five attributes relate to all of these three challenges. The literature review also identifies three specific goals for the development of pillar two instruments: competitiveness, sustainable management of natural resources and balanced territorial development. The selected attributes capture these objectives.

Each choice card consisted of three alternatives; the first alternative defined the current situation of the CAP's budget structure in terms of the mentioned funding instruments, whilst the remaining alternatives presented variations of this budget structure relative to the current situation. For every attribute, the possibility of both increases and reductions in budget shares has been considered. Table 1 shows an example of a typical choice card presented to respondents. The remaining alternatives to the current situation have been created through variations in the percentage of the budget allocated to each attribute.

The set of attributes and levels constitutes a full factorial design with $(8^3*4^2) = 8192$ combinations. By means of Bayesian efficient design[iii], based on the minimization of the D_b-error criterion, we reduced this number to 32, which in turn have been blocked into eight groups of four cards. It is important to note that the magnitude of the total budget is constant for all alternatives[iv]. The alternatives differ only in the share that is allocated to the different attributes. The best fraction of the design was obtained from a set of candidate designs using the software NGENE V.1 (for a general overview of efficient experimental design literature see Rose et al. (2011) and references cited therein).

After *each* choice task, respondents were inquired about which attributes they had ignored. Additionally, respondents were asked to indicate if one or more of the alternatives were ignored, because it contained an unacceptable attribute level, and in case of a positive response they were further probed, which attributes and levels they considered unacceptable. This information was used to model non-attendance to alternatives.

Data were collected in three provinces of Andalusia[v], Spain (Figure 1), between March and June 2011 in 370 face-to-face interviews with adults 18 years of age or older. To ensure the regional representativeness given the limited budget available, the sample was first stratified according to rural, urban, and metropolitan place of residence. The second stage of the sampling procedure involved the sampling of individuals within each of these three areas according to age, gender, and educational level according to INE-Spanish Statistical Institute (2011).

Methodology

The model chosen for the parametric analysis of responses is a latent class (LC) model, an approach which has grown rapidly in popularity with discrete choice modellers[vi]. The latent class approach makes use of two sub-models to determine the probability of choice. One is for class allocation, and estimates the probability of each individual to belong to the specified classes usually as a function of respondents' individual-specific characteristics. The other sub-model determines the class probabilities conditional on the tastes within each class. The actual choice probability for individual *n* and alternative *i* is given by a sum of the class-specific choice probabilities, weighted by the class-allocation choice probabilities for that specific individual, as specified in equation 1:

$$P_n(i) = \sum_{s=1}^{S} \left[\frac{\exp(\alpha_s Z_n)}{\sum_{s=1}^{S} \exp(\alpha_s Z_n)} \right] \left[\frac{\exp(\beta_s X_{ni})}{\sum_{j=1}^{J} \exp(\beta_s X_{nj})} \right] \qquad s = 1, \ldots.., S, \quad \alpha_S = 0. \tag{1}$$

where the first expression in brackets represents the probability of observing the individual *n* in class *s* (being Z_n his socio-demographic characteristics), and the second terms describes the probability of choosing alternative *i*, amongst the *J* alternatives contained in the choice card, conditional on belonging to class *s*.

In LC modelling the number of latent segments must by imposed exogenously by the analyst. There is no rigorous way to select the number of classes, and several ways have been proposed in the literature, such as the Akaike Information Criterion AIC, and the Bayesian Infomation Criterion BIC (Allenby, 1990). The number of classes that minimises each of the measures suggests the preferred model. As Swait (1994) points out, these criteria should be used as a guide to assist in determining the number of classes, but generally applicable rules for this purpose do, however, not exist. Analyst judgement, model parsimony and obtaining a behaviourally meaningful outcome play a role in the final model selection. For example, Scarpa and Thiene (2005, 2011) note that the chosen number of classes should be conditioned by the significance of parameter estimates and requires the analyst's own judgement on the meaningfulness of the parameter signs. As mentioned in Scarpa and Thiene (2011), similar conclusions and suggestions have been made by Hynes et al. (2008) and Ruto et al. (2008). In this study, the AIC and BIC criteria advocate for the use of either 2 or 3 classes[vii], depending on the model incorporating ANA-behaviour and exclusion of alternatives due to the presence of unacceptable attribute levels. We opted for the two class model in this study based on considerations regarding the signs and significance of parameter estimates and based on concerns about low class probabilities for individual classes in some of the three class models. Furthermore, the two class model provides a clear behavioural interpretation of the resulting coefficients of the classes.

When estimating the models, an identification issue arises from the constraint of a constant budget in all the alternatives. Given this linear constraint, there are only four degrees of freedom for the five attributes employed, so that one attribute must be omitted from the model specification for identification purposes. Therefore, the estimated model coefficients have to be interpreted as the difference in marginal utility of an attribute and the marginal utility of the omitted attribute[viii]. This model specification allows for the estimation of marginal rate of substitutions between attributes. However, it would not offer an immediately accessible behavioural interpretation of the resulting coefficients. Because of that, we reclassified the attribute levels into a set of dummy variables. Two dummy variables were created for each attribute, which indicate whether the attribute level specified in an alternative is lower or greater than the level used in the reference alternative[ix]. The resulting coefficients have an intuitive meaning. They reflect the marginal utility that the respondents of a particular class derive from an increase or reduction of the budget share spent on a particular CAP measure. As such, this model specification enables the generation of highly policy-relevant information that can be used to inform for the design of the future CAP, given that it represents the marginal utility that society derives from changes to the budget share currently dedicated to a particular instrument.

To demonstrate the impact of ANA on model performance, we estimate and compare ten different models (see Table 2 for a summary of the strategies used in the models). Model 1 represents the standard approach in DCE and hence does not account for ANA, i.e. all attributes are assumed to be fully considered by respondents in the choice process. Model 1 serves as a benchmark for comparison with the other models. Model 2 and 3 follow the approaches previously used in the literature to address ANA at sequence and choice task level, respectively. For model 2, ANA at sequence level was reconstructed from stated responses at choice task level assuming that a respondent would have reported an attribute as 'ignored' if s/he had stated to having ignored the attribute on *all* choice occasions. In order to investigate the implications of this assumption for comparisons of choice task and sequence level ANA, we estimate two additional models (Models 4 and 5 in Table 2). For these models, sequence level ANA was reconstructed assuming that an attribute was ignored if respondents declared to have ignored it in at least 75% (Model 4) and 50% (Model 5) of the choices (i.e. in three, or two out the four choices s/he made). In all the models where ANA is considered, we assigned a zero utility to the non-attended attribute, assuming that respondents assign zero marginal utility to those attributes that were reported as ignored[x].

These five models were extended to incorporate the case of non-attendance to alternatives due to the presence of one or more attribute levels that are outside the respondents' acceptable choice bounds. In this case, we assume that respondents did not focus on the value of the other attributes of the alternative containing unacceptable attribute levels. Therefore, we constrain the utility associated with the attributes of the alternative in the likelihood function to zero and include a dummy variable taking one if the alternative contains an unacceptable attribute level in the utility specification. This approach entails the general notion of Swait's (2001) attempt to incorporating non-compensatory decision rules via attribute cutoffs into discrete choice models. Cutoffs represent attribute level thresholds for a respondents which, if 'violated', have implications for the utility derived from affected alternatives. In the case of 'hard' cutoffs, the utility of an alternative is assumed to be zero, while a 'soft' cutoff would imply a utility penalty to be imposed on an alternative to reflect the reduced probability of choosing an alternative in the presence of unacceptable attribute levels. Because attribute cutoff information was obtained explicitly in relation to non-attendance to alternatives in our study, one option for analysis would have been to completely omit alternatives with unacceptable attribute levels from the analysis ('hard' cutoff). However, respondents may err on their stated cutoffs, or choose to violate them under certain conditions. As Swait (2001, p. 907) notes, "in some sense, decision makers have a 'fuzzy view of cutoffs: when forced to, they will violate a self-imposed 'constraint'". Therefore, we removed all attribute information for the affected attributes and included an alternative specific dummy that is equal to one when the alternative contains an attribute level deemed unacceptable for respondent. This dummy variable captures the 'utility penalty' associated with the presence of unacceptable attribute levels in an alternative, and by doing so reflects the reduced likelihood of such an alternative to be chosen.

Model 6 incorporates only non-attendance to alternatives. Models 7, 8, 9 and 10 consider non-attendance to alternatives in addition to ANA. These models reflect the two stage decision process outlined above, where respondents first omit alternatives which contain unacceptable attribute levels and subsequently make their choice between the two remaining alternative based on compensatory behaviour and/or ANA[xi]. Table 2 summarizes the different model approaches used to account for ANA and alternative non-attendance.

Results and Discussion

Table 3 reports the frequency of attendance to each attribute as declared by respondents. The frequency of attribute attendance varies greatly across the attributes. Respondents focused on the whole set of attributes in only 5% of the total choices made. Respondents were most likely to 'always consider' the Direct Payments (40%), and Agri-Environmental Payments (25%). In contrast, the support to rural areas for assuring a diversification of rural economy was the most ignored attribute. It has been ignored by the 73% of the sample across all choice situations. Possibly, citizens do not approve that the development and diversification of rural areas is an issue that has to be funded via CAP, and think that it should be undertaken with other structural policies funded with the European and regional development or cohesion funds.

Inspection of the percentages in table 3 underlines that ANA is common, which is in line with previous research. The figures suggest that it is more likely that respondents, who ignore an attribute in one choice situation, will also ignore it the subsequent one. However, there is considerable variation in the number of choice situations where an attribute has been ignored, and across all attributes only ‘Payments to farmers in less-favoured areas’ and ‘Quality of life in rural areas and diversification of the rural economy’ are ignored in all choice situations by more than 50% of respondents. This clearly indicates the importance of observing ANA behaviour at choice task level rather than at choice sequence level. It also cautions against the reconstruction of serial non-attendance following the approach used by Scarpa et al. (2010) and Meyerhoff and Liebe (2009), who assume that an attribute would only have been declared as ‘ignored’ if it has been ignored throughout the whole sequence of choices. Since the response to a serial ANA question is unknown to the analyst, this strict assumption could result in an under-representation of ANA behaviour, for example if respondents would have used a majority rule to state which attributes have been ignored in the choice task.

Non-attendance to alternatives due to unacceptable attribute levels occurred in 13.8% of the choices. Two attributes were particularly prone to it: ‘Direct aid’, was declared unacceptable most frequently because it was considered too high, followed by an unacceptable reduction of ‘Agri-Environmental Payments’. In the majority of cases (90%) of alternative non-attendance, unacceptable attribute levels were reported for a single alternative. In the second step of the choice process, i.e. after eliminating the alternative which contained an unacceptable value from the choice set, a compensatory decision rule including all attributes was only applied by a single respondent. This result clearly show that non-attendance to alternatives and ANA coexisted as decision strategies in the choice process, and again highlights that a fully compensatory decision rule is employed in only a small percentage of choices. The remainder of respondents, who declared an unacceptable level (10%), reported that it applied to two out of the three alternatives. Therefore, they employed a pure EBA choice strategy.

A series of models were estimated to investigate the impact of alternative strategies of accounting for non-attendance to alternatives and attributes. A total sample of 1480 choice observations was used for model estimation. Table 4 reports the results for the ten models investigated[xii].

All models are highly significant and show a good fit to data. Class membership probabilities for the two classes are similar across the different model specifications. With the exception of the baseline model, the probability of class 1 is around 60% and the probability of class 2 is around 40%. Class membership is found to be explained by whether respondents have a relative whose economic activity is related to farming[xiii]. Respondents, who have a relative whose economic activity is directly related to the agricultural sector, are more likely to belong to class 2. Significance, magnitude and sign of this parameter (Fam.-Agri.) are not statistically different across all the models.

Turning to the preference parameter estimates, the sign of significant coefficients remains the same across the different models[xiv]. However, the statistical significance of some individual coefficients varies for some of the models when ANA or both ANA and non-attendance to alternatives are taken into account. Preference parameters have to be interpreted relative to the current situation of CAP budget share with respect to the five considered CAP instruments. In class one, respondents prefer a reduction of the budget allocated to direct aid (AD-less) in favour of the other measures, in particular in favour of an increase in the share allocated to environmental care (ENV-more) through agri-environmental measures. A reduction of the payments to less-favoured areas (LFA-less) and to promote the competitiveness of the agricultural sector (CP-less) is associated with disutility. Preference patterns towards the funding of other, non-agriculturally focused activities in rural areas (RD) are found to differ in the alternative model specifications employed. In particular, a reduction of the budget allocated to this measure (RD-less) is positively evaluated in model 1, negatively evaluated in model 3 and points to indifference (parameter not significantly different from zero) in the models where serial ANA is considered (models 2, 4, and 5). These differences show that preference parameters can be considerably affected by the treatment of different attribute processing strategies in the models, and it illustrates how the modelling approach can impact on policy conclusions based on model results. Given that model 3 outperforms the other models, the analyst can conclude that citizens derive disutility, (and not utility as suggested by the standard model) from a reduction of the funds dedicated to the development of non-agricultural activities in rural areas.

Compared to class one, respondents who belong to class two have opposite preferences for the 'Direct Aid' attribute and prefer an increase of these funds while disliking a reduction. This is expected given that direct aid payments are income support payments, which farmers receive under the current CAP simply for "being farmers". To be entitled to these payments under the current regulation, farmers have to comply with basic regulatory standards. These standards do not impose a challenge to most farmers (for example, one standard requirement is 'to keep the land in good agricultural and environmental condition (GAEC)). Preferences for the other attributes are similar to the ones of class one. The coefficients for the 'Agri-Environmental Payments' attribute are not significant in model 1, while they are highly significant in the remaining models. In fact, model 1 has the lowest number of significant attribute parameters (13 out of 20) of all models employed. This demonstrates the importance of considering attribute processing strategies to obtain unbiased preference parameters and to provide a more realistic description of citizens' preferences.

The consideration of ANA statistically improves models performance. Relative to the benchmark model, all models which incorporate ANA show large increases of the LL function at convergence and a better the fit to data. Commenting first on the models, which take into account ANA at serial level (models 2, 4 and 5), the different assumptions made for reconstructing the ANA from choice task level to choice sequence level significantly affect model statistics. In particular, on statistical grounds the best model is obtained when we assume that an attribute should be treated as ignored when it has been declared as ignored in at least 75% of the choices. Although this result is clearly specific to the dataset at hand, the general message is clear: when the analyst wishes to compare ANA at choice task level and choice sequence level, it is misleading to simply assume that a respondent would have reported an attribute as 'ignored' only if s/he had stated to having ignored the attribute throughout the *whole* sequence of choices. The results show that such a strong assumption does not hold, and hence some caution is warranted regarding the conclusion of Scarpa el al. (2010): that the benefits of considering ANA at choice task level in terms of model performance and efficiency of WTP estimates may outweigh the additional efforts associated with requesting ANA statements after each choice task instead of only once at the end of the choice sequence.

However, the model taking into account choice task specific ANA clearly outperformed all the other models that allow for different assumptions regarding the reconstruction of serial ANA. This result comes as no surprise after analyzing the heterogeneity of ANA as show in Table 3. It provides us with more confidence that the conclusions of Meyerhoff and Liebe (2009) and Scarpa et al. (2010), that ANA should be considered at choice task rather than at sequence level, are indeed valid. This fact may be exploited for the future design of DCEs, especially in an agricultural and environmental context. When ANA is present for all attributes but varies in frequency across attributes and choice situations, it has signals that respondents focused on different sets of attributes throughout the sequence of choices. When researchers face the question whether they should elicit ANA at choice task or choice sequence level in the study design, information about the degree of heterogeneity of ANA behaviour with respect to a specific good or service in question could be collected at choice task level in pre-tests or the pilot study. A large degree of heterogeneity of stated ANA behaviour across the different attributes would advise for disclosing ANA at choice task level, despite the extra survey cost involved. Asking for ANA behaviour directly after each choice task minimises recall errors and provides a direct link to the behavioural process that the analyst aims to understand (Alemu et al., 2012). However, and importantly, disclosing ANA at choice task level may affect the respondent's posterior choice behaviour, for example by inducing an expectation to attend. With the data available and the design of this study we cannot formally test whether this happened. Testing would require a comparison of results of a two-stage survey, where attributes identified as unimportant by respondents in the first stage are eliminated in the second stage. To the best of our knowledge, there is only one published paper which carried out a similar study (Hess, 2012). This paper finds no systematic differences between first and second stage estimates.

When disclosure at choice task level is not possible (for example, due to time limitations), our model results show that there may still be considerable gains in model fit from taking ANA at sequence level into account. In this respect, information on frequencies of ANA across attributes and choice situations may be useful to inform the design of the follow-up question used to determine ANA at sequence level. The follow-up question typically used for this purpose may be made more specific in terms of the definition of (non)-attendance. For example, respondents may be offered the option to differentiate between having always, sometimes or never ignored an attribute as suggested by Colombo et al. (2012).

We now turn to the description of those models, which incorporate the exclusion of alternatives as a result of the presence of unacceptable attribute levels in addition to ANA (Models 6 to 10). All models are statistically superior to the parallel models, which only take ANA into account. Generally, the incorporation of non-attendance to alternatives does not affect class probabilities and the signs and statistical significance of the class utility parameters (although some coefficients either increase or decrease in levels of statistical significance).

The comparison of model 1 and model 6 illustrates the net contribution of non-attendance to alternatives. Model 6 shows an important increase of the LL function over model 1 (57.2 units with 2 additional parameters) and a moderate increase in the rho-square value. The dummy variable created to capture the utility penalty associated with an alternative containing an unacceptable attribute level is negative and significant in both classes. This indicates that such an alternative is associated with a negative utility value, which reflects a highly reduced probability of such an alternative to be chosen in the model. This result holds in all the models except model 7 and model 9, in which the parameter is insignificant in class one.

Compared to models that considered ANA alone, all the models, which additionally consider attribute exclusion triggered by the presence of unacceptable attribute levels , also show improvements in terms of statistical performance. By jointly modelling ANA and non-attendance to alternatives, it is therefore possible to explain a larger degree of the choice variability. Most of the respondents, who reported unacceptable attribute levels ruling out the choice of an alternative, adopted an ANA decision rule to select the preferred alternative between the two remaining alternatives. Non-attendance to alternatives can be an independent and stand-alone decision process, but this result shows that it is probably more relevant as a complementary decision process, which coexists together with ANA behaviour. This underscores that respondents act in a rationally adaptive manner by making use of several choice decision strategies together as a means of simplifying the cognitive burden of the choice task. Accordingly, model 8 (joint consideration of ANA at choice task level and non-attendance to alternatives) outperforms every other model with a LL function increased by 22 units and a 2% increase of the rho-square value relative to model 3 (ANA at choice task level alone).

Conclusions

As observed in previous research, respondents do not attend to all attributes within DCEs and make use of different attribute processing strategies to simplify their choices. Amongst these attribute processing strategies, we find that ANA is a principal one. However, ANA may occur jointly with other decision rules.

In this paper, we report evidence that suggests that ANA and non-attendance to alternatives due to the presence of unacceptable attribute levels are two independent choice strategies in DCEs, which can coexist. If an alternative contains an attribute level, which lies outside the choice bounds of a respondent, we assume that s/he chooses the preferred alternative in a two step process. In the first step, the alternative with an unacceptable attribute level is omitted from the choice set. Therefore, the second step focuses on the remaining options. The final choice among the remaining alternatives typically includes only a subset of attributes and hence shows ANA behaviour.

A large degree of ANA heterogeneity is observed within the sequence of choices carried out by a single respondent in addition to heterogeneity in ANA behaviour between respondents. This heterogeneity can only be identified by monitoring ANA at choice task level. Taking information at the choice task level into account resulted in large gains in model performance.

In DCE surveys, monitoring for ANA in the decision process can take place at choice sequence level or at choice task level. Potential gains from analyzing ANA at choice task level are related with the large intra-respondent heterogeneity in attribute attendance. The descriptive results from the survey data used in this paper are powerful in demonstrating that both intra- and inter-respondent heterogeneity in ANA behaviour is large. Because information on intra- and inter-respondent heterogeneity of ANA occurrence is a good indicator for expected gains in terms of model performance, we recommend that future studies should regularly obtain such information in pre-tests and pilot studies to inform the decision on whether to monitor for ANA at choice task or choice sequence level in the main survey.

Significant improvements in model performance are observed when the different possible choice strategies are considered in the model specification and estimation. Importantly, we find some differences in the level of statistical significance and sign of the utility parameters. This suggests that the standard approaches used to model DCE data, ignoring different attribute processing strategies, may result in inaccurate expressions of the utility function, which may bias key outputs of DCE studies, including policy recommendations and welfare measures.

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Table 1: Example of choice card

ATTRIBUTES	**CURRENT SITUATION**	**ALTERNATIVE 1**		**ALTERNATIVE 2**	
Direct Payments	65 %	↓	62 %	↑	74 %
Payments to farmers in less favoured areas	1 %	=	1 %	↑	4 %
Agri-environmental payments	11 %	↑	14 %	↓	2 %
Quality of life in rural areas and diversification of the rural economy	2 %	↑	5 %	=	2 %
Improving the competitiveness of the agricultural and forestry sector	21 %	↓	18 %	↓	18 %
¿Which alternative do you prefer?	□	□		□	

Table 2 Approaches used to model attribute attendance

	Model									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
ANA not considered	X	-	-	-	-	X	-	-	-	-
Serial ANA: Ignored in at least 50% of the choices	-	-	-	-	X	-	-	-	-	X
Serial ANA: Ignored in at least 75% of the choices	-	-	-	X	-	-	-	-	X	-
Serial ANA: Always ignored	-	X	-	-	-	-	X	-	-	-
Choice task level ANA	-	-	X	-	-	-	-	X	-	-
Non-attendance to alternatives	-	-	-	-	-	X	X	X	X	X

Table 3: Respondents' self-reported attribute attendance (values express %)

Attribute	**Always Ignored**	**Ignored 75% of the time**	**Ignored 50% of the time**	**Ignored 25% of the time**	**Always Considered**
Direct Payments (AD)	21.9	8.9	12.4	17.0	39.7
Payments to farmers in less favoured areas (LFA)	56.8	23.2	8.1	3.0	8.9
Agri-environmental payments (ENV)	32.4	16.8	11.1	14.9	24.9
Quality of life in rural areas and diversification of the rural economy (RD)	73.0	13.8	5.7	3.0	4.6
Improving the competitiveness of the agricultural and forestry sector (CP)	36.2	21.4	13.5	13.0	15.9

Table 4: Modelling results

Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**
Utility coeff. Class 1										
Constant						-6.648*	-11.053	-16.887**	-12.087	-13.634**
AD-less	1.564***	3.676***	4.256***	3.03***	2.811***	1.705***	3.862***	4.61***	3.203***	2.769***
AD-more	-1.027***	-3.972***	-4.183***	-3.685***	-2.768***	-0.803***	-3.15***	-3.596***	-2.929***	-2.223***
LFA-less	-1.381***	-1.233	-11.16*	-4.865	-5.142***	-1.381***	-3.936	-9.006	-3.934	-5.562***
LFA-more	-0.162	0.943	3.702***	3.56***	1.972***	-0.221	17.15***	3.913***	3.327***	2.287***
ENV-less	-1.442***	-4.131***	-5.023***	-3.958***	-3.791***	-1.492***	-2.534***	-4.804***	-3.989***	-3.317***
ENV-more	0.528**	2.428***	3.443***	2.018***	1.816***	0.476*	2.716***	3.188***	2.165***	1.898***
RD-less	0.814***	-12.033	-3.308**	-3.666	-2.792	0.86***	-20.057***	-4.443**	-0.826	-1.775
RD-more	0.606***	-11.976**	4.518***	2.216***	2.223***	0.732***	1.778***	4.593***	2.352***	2.442***
CP-less	-0.547***	-11.309***	-5.324***	-4.289***	-2.156***	-0.409*	-5.128***	-5.86***	-4.361***	-1.94***
CP-more	0.360	2.024***	2.400***	2.17***	1.303***	0.535**	1.978***	2.966***	2.595***	1.457***
Utility coeff.Class 2										
Constant						-2.805***	-3.345***	-4.623***	-3.182***	-4.347***
AD-less	-1.303***	-2.417***	-2.541***	-2.13***	-1.806***	-1.168***	-2.59***	-2.465***	-2.126***	-1.737***
AD-more	0.813***	0.947***	1.141***	0.845***	0.91***	0.826***	0.925***	1.212***	0.936***	1.074***
LFA-less	-0.667**	-2.601**	-2.658***	-1.173	-2.366***	-0.476	-0.267	-1.921***	-0.353	-1.66**
LFA-more	0.801***	3.824***	1.501***	1.187***	1.301***	0.829***	0.548	1.52***	1.273***	1.262***
ENV-less	-0.356	-1.978***	-2.184***	-1.672***	-1.304***	-0.285	-2.22***	-2.068***	-1.548***	-1.242***
ENV-more	0.079	1.203***	1.287***	1.339***	0.888***	0.323	1.395***	1.47***	1.522***	0.922***
RD-less	-0.751**	-0.655	-1.39**	-0.472	-1.095*	-0.734**	0.105	-1.529**	-0.831	-1.426**
RD-more	-0.015	0.731*	0.201	-0.705	0.213	-0.058	-1.872**	0.003	-1.587**	0.009
CP-less	-0.371	-0.382	-0.998***	-0.73**	-0.81***	-0.473**	-0.943**	-1.002***	-0.691**	-0.868***
CP-more	0.298	0.963**	1.601***	0.966***	0.934***	0.328	1.151***	1.618***	1.045***	0.983***
Class Membership										
Constant	0.169	-0.15	-0.109	-0.156	-0.162	0.03	-0.052	-0.148	-0.119	-0.092
Fam.-Agri.	0.761***	0.661**	0.725***	0.814***	0.838***	0.758***	0.632**	0.736***	0.803***	0.786***
Class probabilities										
Class 1	0.66	0.57	0.59	0.59	0.59	0.62	0.59	0.58	0.60	0.60
Class 2	0.34	0.43	0.41	0.41	0.41	0.38	0.41	0.42	0.40	0.40
Model Statistics										
N	1480	1480	1480	1480	1480	1480	1480	1480	1480	1480
LL	-1302.8	-1160.8	-838.4	-1061.2	-1083.3	-1246.6	-1105.5	-815.7	-1010.48	-1039.52
Pseudo ρ^2	.20	.29	.48	35	.33	.23	.32	.50	.38	.36

Figure 1: Map of the study area

[i] As a referee pointed out we acknowledge that strictly speaking non-attendance to alternatives would only apply to labelled CEs, where respondents use labeling information to omit an alternative from the choice set without focusing on its attribute levels. In the case of a generic CE, such as the CE described in this article, the exclusion of alternatives is triggered by the presence of attribute level(s) which are deemed unacceptable to respondents. This implies that respondents screen the alternatives first and hence 'attend' to them in some form. However, both of the above cases result in an elimination of alternatives from the choice set, which is to be taken into account when modelling the choice process.

[ii] With k quantitative attributes, a 2^k rule for the combinations of ANA applies. Given the number of attributes used in this study, 32 classes are required to capture all possible combinations. If preferences heterogeneity is considered and modeled discretely, the number of necessary classes would increase further. In the case of considering a continuous distribution of taste heterogeneity for each attribute in addition to ANA patterns captured in latent classes, for example in a combined latent class-mixed logit specification (Hess et al. 2012), compromises need to be made on the number of ANA patterns analysed to ensure an adequate class size required for the identification of random taste heterogeneity within each class. With the typical sample size used in environmental valuation contexts, striking this compromise can be challenging.

[iii] The priors for the design were obtained from a pilot study of 20 people.

[iv] It would not be credible to assume that the EU commission would increase the total budget in the next period (2014-2020), relative to the budget available in the current period (2007-2013).

[v] Granada, Seville and Malaga were the chosen provinces. These provinces concentrate the majority of the Andalusian population. They also show a different pattern of 'rurality'. In particular, Granada is the most rural province with 53% of people living in rural areas, 21% in urban and 26% in metropolitan areas. Malaga is the most urban province with 85% of people living in metropolitan and urban areas and just 15% living in rural dwellings. Seville province lies in between.

[vi] In this paper we only provide a short description of the latent class model acknowledging the existence of an abundant literature, which describes its underpinnings. The reader interested in a more detailed description of the model, and its comparison with other models, may refer to, for example, Boxall and Adamowicz (2002) and Colombo Hanley and Louviere (2009).

[vii] This happened in six out of the ten models described where the BIC criteria advocate for the two class solution and the AIC for the three classes solution.

[viii] The generic alternative *i* can be expressed as: $U_i= \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5$. However, given that the sum of the budget is fixed to 100 in all alternatives $X_5 = (100- X_1 – X_2 – X_3 – X_4)$, so that the resulting utility for alternative *i* is equal to $U_i= (\beta_1-\beta_5)X_1 + (\beta_2-\beta_5)X_2 + (\beta_3-\beta_5)X_3 + (\beta_4-\beta_5)X_4$.

[ix] In this specification, dummy variables represent more than one attribute level (for example, the dummy for "Increase in Direct Aid" is equal to one for all the values greater than 65%). This implies that we relax the linear constraint imposed by the constant budget in the estimation of the model.

[x] In the literature, there are mixed results about the consistency of self-reported ANA with the assumption of zero utility. For example, Scarpa et al. (2009) and Carlsson et al. (2010) found that respondents, who stated to having ignored an attribute, had not *completely* ignored it. This may point to low instead of zero taste sensitivities for attributes. However, these studies assessed ANA at sequence level, and may therefore have erroneously assumed that stated responses always coincide with ignoring an attribute across the whole sequence of choices. On the other hand, Balcombe et al. (2011) and Colombo et al. (2012) found evidence that corroborates the assumption of zero marginal utility for attributes that had been declared as ignored by respondents.

[xi] It is possible that two alternatives contained an unacceptable value. In this case, a pure EBA decision strategy applies.

[xii] Due to limited space, we do not report models, for which we reconstructed serial attendance assuming that attributes would have been declared as not attended if they were ignored it at least once across four choices. Of course, full model results are available from authors upon request.

[xiii] A set of covariates (age, gender, education, income) were tested in previous analysis and omitted from the final model specification, because they were not statistically significant.

[xiv] The only exception is the coefficient of RD-Less, which is positive and significant in the models that do not consider ANA (model 1 and 6) and negative and significant in some of the models which do take ANA into account (models 2, 7 and 8)